Optimal Allocation Algorithm for Sequential Resource Allocation in the Context of Food Banks Operations

By

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Abstract

This thesis studies a Sequential Resource Allocation (SRA) problem that is faced by food distribution of a nonprofit organization (e.g. food banks). Different from commercial operations' objective aimed at maximizing profit, the primary objective arising in nonprofit organizations is to fairly satisfy the demand of recipients. Rising demand and limited resource increase the importance of effective food allocation operations that maximize equity and resource utilization at the same time. In the context of food bank operations, we consider the problem of collecting an uncertain quantities of donation and allocating them sequentially to meet customers' demands that are uncertain until arriving at the customer's location. A SRA model is formulated that can be used to design an optimal visiting route; it focus on equity maximization and waste reduction. Without considering travel cost/time restriction, our work solves the problem by developing a new objective function to minimize the filling rate (i.e., the ratio of the allocation quantity to observed demand) gap among agencies. An experimentation is designed to evaluate and analyze the performance of the algorithm, and the proposed method yield better solutions in terms of waste reduction. Furthermore, by using adaptive large neighborhood search (ALNS), we extend the model to include travel cost into consideration to find a near-optimal visiting route. A case study with larger scale is also performed that shows the algorithm obtains high-quality solutions in terms of equity and efficiency (travel costs).

Dedication and acknowledgements

My thanks and appreciation to Oliver Gao for persevering with me as my advisor throughout the time it took me to complete this research and write the dissertation. The inspiration for doing the research came from the Food Bank of Southern Tier program he headed at Cornell University. Also, I gratefully acknowledge the data provided by the Food Bank of the Southern Tier.

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Author's declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

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Chapter 1

Introduction

Despite the fact that America has the strongest national economy with a GDP of 17.95 trillion USD in 2017 (BEA [2017]), the average percentage people living in poverty conditions is 12.7 percent of its population(Semega et al. [2017]). Based on the most recent hunger study from Feeding America (FA), 45 million Americans rely on FA and their network of pantries, shelters, and soup kitchens for food (FeedingAmerica [2017]). The largest suppliers to these agencies are regional and local food banks. Food banks are large distribution centers that collect, store, and distribute food to agencies locate in different places within a county to serve needy people. The goal of FA and the agencies in their network is to match donated food with those in need. This matching between supply and demand has created challenging problem for food banks to ensure good service to needy people. This problem can be described as a combination of supply management and route optimization problem that occurs each day at thousands of nonprofit agencies across the country.

Food bank systems are complex systems with large number of externalities and non-standard challenges, mainly due to the large number of operations a food bank undertakes every day. Dispatching loaded vehicles to serve agencies is one of the most essential and daily operations of a food bank. Given the fact that a food bank has limited supplies to be distributed among a set of agencies, the food bank needs to decide the share of each agency and the sequence of a vehicle visits during routing. The complexity of this challenging problem lies in the sequentially observed demand that is unknown in advance. Furthermore, given a goal of a food bank to maintain equity among served population and minimize food waste rather than maximizing profit or minimizing cost, the problem becomes more difficult. Hence, this study is dedicated to study the problem of optimally dispatching a fleet of vehicles to serve certain number of agencies under given probability density function of agency's demand.

The Food Bank of Southern Tier, a member of Feeding America, serves a six-county area in New York (see `https://www.foodbankst.org/`). The branch has been distributing food and other grocery products to people in need through a network of more than 160 partner agencies in Broome, Chemung, Schuyler, Steuben, Tioga and Tompkins Counties. In the fiscal year 2016, the branch distributed 11,553,304 pounds of food and grocery items to the partnering agencies serving needy people. The partnerships between the food bank and its member agencies across service area is crucial to the food allocation mission as they ensure the food they acquire and distribute gets to the people who need it most.

A food bank receive a call from donor informing them that they have food items to be collected by the food banks. The food bank then sends a truck to collect the food then dispatch it to visit all the agencies. Generally, the quantities of donation or demand are not known until the truck arrives the sites due to timing or staffing constraints of the agencies. After the demand is made by the agency, the decision maker (e.g. the driver) decides the allocation quantity to meet the demand while reserving food for the agencies to be visited.

To this end, we present a decision support tool that assists food banks in deciding equitable and effective optimal dispatch policies for their fleet of vehicles under uncertain supply and demand. In our work, different from using filling rate of agency's demand as a function of satisfaction in Lien et al. [2014], we use the gap of filling rate instead. Clearly, the problem is then to decide the optimal quantities of food items to be provided for each agency and the optimal visiting routes of vehicles. In our model, the decision on allocation quantity is made by applying Two Node Deposition (TND) allocation heuristic used in Lien et al. [2014].

We then classify the problem into two settings. In the first setting, we define the problem as SRA problem with a new objective function, which is discussed in detail in 3. Without considering travel constraints, we need to searching every possible routes t find the best visiting sequence. The second setting is the situation where travel costs or travel time is considered. We develop a utility function to valuate the solution and we adjust Adaptive Large Neighborhood Search (ALNS) algorithm to find and determine the optimal visiting sequence.

The remainder of this thesis is outlined as follows. Chapter 2 summarizes the related literature. Chapter 3 describe the SRA problem and our solution approach. The SRA problem involving travel constraints and its solution is discussed in Chapter 4. Chapter 5 presents conclusion and identifies areas for future research.

Chapter 2

Literature Review

The World Food Programme (WTP), a leading humanitarian organization, has been committed to end hunger, achieve food security and improved nutrition. The international community predicts that by 2030, one in nine people worldwide still suffer from food insecurity. Food and food-related assistance including food supply chain lie at the heart of the effort to break the cycle of hunger and poverty. Much work has been done in commercial supply chain area. In general, models designed for resource allocation or inventory management in the commercial settings are aimed at maximizing profit or minimizing cost. Some research on non-profit operations have similar objectives to maximize utility or minimizing costs. Nonprofit operations differ from commercial sector organizations in terms of their source of supplies, goals, performance metrics, and level of risk and uncertainty. Providing equal service is an important component of their objectives, hence equity is a special aspect of decision making in the nonprofit operations in addition to efficiency-related(Balcik et al. [2010]). More recent research in nonprofit settings in focused on improving equity.

2.1 Challenges of resource sequential allocation

To assist food banks in allocating uncertain supplies in a equal way and measure the performance of the distribution efforts, several allocation rules are designed to realize optimal equity. Proportional allocation (PA) policy is addressed by Karaesmen et al. [2011]. According to the policy, quantity distributed to each agency is determined by the ratio of their poverty population. Additionally, Serve largest demand first (SLDF) and serve smallest demand first (SSDF) are also proposed for the objectives of food allocation in nonprofit operations.

Fianu and Davis [2018] formulate the decision problem as a discrete-time, discrete state Markov decision process based on the perspective of a single branch in the food distribution network. Equity is defined as a function of the pounds distributed to per person in poverty(PPIP) in their work. They develop a formulation for a single commodity inventory system with periodic review. Their findings proves that allocating supply to each area in proportion to its poverty population realizes equity maximization.

Orgut et al. [2016b] developed a linear programming model to determine effective and equitable distribution of donation for a food bank. Their model considers the receiving capacities of the agents and develop policies that minimize the amount of undistributed food while maintaining equity. She considered stochastic capacity of the agents with deterministic supply, however, the supply and demand were assumed to be deterministic which does not represent the real-life situation; in fact, demand is highly uncertain in practice.

Lien et al. [2014] introduced a sequential allocation problem, the object of which is focused on ensuring equity and achieve waste reduction. They work with the Greater Chicago Food Depository, an active FA member, to distribute perishable food from donors to agencies. To address the unique problem motivated by the FRP (Food Rescue Program), they develop a new model and solution approaches aimed to maximize the expected minimum fill rate on a fixed route. They characterize the structure of the optimal SRA policy along a route using stochastic dynamic programming, and show that the visiting sequence may significantly affect equity. Therefore, they develop heuristics that result in near-optimal sequencing and allocation policies for the single-route problem. Given a set of nodes, sequencing nodes in decreasing order of coefficient variation given a set of nodes is ideal to meet the near-optimal equity, and when coefficient variations are identical, nodes can be ordered in decreasing standard deviation. However, the waste is not always reduced by improving the minimum filling rate within a rote, and the sequencing policy that aimed to filling-rate maximization may result in great travel costs. Therefore, better solutions can be developed when taking waste and travel costs into consideration.

Performance metrics is critical to find the optimal solution. Although objectives that are based on efficiency serve the objectives of commercial distribution problems, sequencing rule in the nonprofit sector often require other objectives that also have impact on the overall performances(Balcik et al. [2010]). Felder and Brinkmann [2002] explore the trade-off between the equity and other objectives such as efficiency in medical services. Orgut et al. [2016a] defines effectiveness is the ability to meet the the demand of the end customer in a route, and equity is referred to allocate resources in a fair way. Balancing between equity and efficiency is tricky and also crucial for nonprofit operations. Campbell et al. [2008] show that minimizing the total travel time or total route length can lead to inequitable response times among demand locations served in a disaster relief situation. Addition to maximizing equity within a single route, Balcik et al. [2014] introduces considers two critical objectives in the context of nonprofit operations, which focuses on equity maximization primarily and considers waste implicitly. They also raise the idea that travel time or travel costs can be the restriction of the solution. Then an efficient decomposition-based heuristic for the problem is developed which incorporate an additional constraint on travel distance or route length.

Obtaining an optimal sequence and allocation policy by the heuristics in the literature is tractable only for small number of agencies. Although Balcik et al. [2014] consider a multi-vehicle sequential allocation problem, the instances have no more than seven agencies. Research can be extended to find optimal solutions efficiently and effectively for larger instances combined with more agencies.

2.2 Research contribution

Our paper contributes to the literature on supply allocation management by introducing a sequential allocation problem with a new object aimed at maximizing equity while reducing waste. We investigate 3 different sequencing rules and measure the performances. We also compare sequencing rules in terms of equity, waste and travel cost.

In the context of food bank operations, although the primary goal is to make fair allocation, the pursue of maximizing expected minimum filling rate may be at high expense of travel time or costs. Due to the fact that only focusing on maximizing equity is not applicable to the situations where traveling cost cannot be ignored. This paper also takes travel costs into consideration, which designed for maximizing equity while limiting travel cost. Instead of isolating the impact of travel cost, we apply adaptive large neighborhood search (ALNS) approach in our model to find a near-optimal sequence which consider both equity and efficiency objectives. By adapting and modifying ALNS algorithm, a near-optimal solution can be obtained more efficiently so that the complexity of finding an optimal sequence with a large amount of nodes is effectively reduced.

Chapter 3

SRA Model

From the perspective of a single branch in the food distribution and allocation network, our modeling framework is single route Sequential Resource Allocation(SRA) problem. The SRA is combined with two problems: the first is the allocation policy determine the quantity allocated to each agency; the second problem is the sequencing policy which determines the positions of agencies along a route. The first problem is solved by the TND Heuristic Allocation addressed in Lien et al. [2014], which is proved to be effective in problems with uncertain donations and uncertain demands.

The sequencing problem is also important to the objective of food allocation operations because sequencing agencies along a route impacts the filling rates. Based on an objective to maximize the expected filling rate, Lien et al. [2014] address a sequencing heuristic that sequencing nodes in decreasing order of coefficient of variations is a ideal sequence, however, the heuristic may result in poor performance in expected waste. Moreover, although the heuristic can ensures effective use of resource if following the TND allocation rule, the waste can be further reduced and a bit reduction may have significant impact on the nonprofit operations. Therefore, we develop a new objective function aimed to achieve maximum equity while reducing expected waste. To test the effectiveness of our new objective function, we do the comparison between the two sequences obtained by TND heuristic and our objective function.

3.1 Problem description

The problem of food allocation is that the exact supply from donors and demand of agencies are uncertain and are not revealed until the driver arrives at a location. Our goal is to make the optimal allocation decision and find the optimal visiting sequence.

Alternatively, we can model the decision making process as a discrete state Markov decision process for a single item, the advantage of which is indicating the optimal way to allocate donated food based on the dynamic supply levels of the trucks.

We assume a warehouse operates several truck routes. The truck collect all donors prior to visiting agencies and returns to the warehouse after serving all agencies. The problem is that the exact supply from donors and demand of agencies are uncertain and are not revealed until the driver arrives at a location. In our model, we assume our trucks have ample capacity to accept all donated food. After an agency make a demand request, the driver has to make the decision on the allocation of food. The driver tries to meet the demand of the agency while reserving supply for the unserved agencies on the route. We make following assumptions for the proposed model:
1. The branch operates a single warehouse, housing several trucks with ample capacity.
2. The state of the system is described as the amount of supply available in the truck at the arrival at an agency.
3. The capacity of the truck is assumed to be unlimited, which means that the state spaces are infinite with lower bound zero and without upper bound.
4. Donations are uncertain until the driver arrives at a donor. Received donations are added to the current available supply.
5. The demand of each agency is uncertain and revealed upon the arrival of the driver.
After arrival at an agency, a certain amount of inventory is allocated to the agency according to the driver's decisions, according to the agency demand observed, supply available and a predefined allocation rule.
6. Given a set of donors and agencies, the driver's decision can be modeled as a sequential resource allocation problem (SRA) . We adapt and adjust the TND Heuristic Allocation Algorithm from Lien et al. [2014], whose objective is to maximize the expected minimum fill rate.

Lien et al. [2014] address the sequential resource allocation problem with a objective that ensure equity by maximizing the minimum filling rate within a route. By using dynamic programming, they develop the two-node decomposition(TND) heuristic which determines the best allocation decision at each nodes given the available supply, current demand, filling rates of agencies already visited and the information of agencies to be visited. The pseudo code for modified TND Heuristic Allocation Algorithm is presented in Algorithm 1, which returns the optimal allocation quantity for each agency, the minimum filling rate and the waste of a route. In the comparison, we evaluate the performances of two different sequencing heuristics based on the same TND allocation algorithm and see whether the combination of our sequencing heuristic and TND allocation algorithm results in better solutions.

Algorithm 1 Framework of TND allocation

input: A scheduled route, agencies' profile and donors' profile

output:Best allocation quantity, minimum filling rate, unused resource after serving all agencies s_{N+1}

Initialize resource available $s_0 = 0$ and minimum filling rate $\beta^0_{min} = 1$
Let n be the counter indicating the number of agencies already been visited
while n<N **do** ▷ N: total number of agencies
    Generate and collect all donations and update s_0
    Determine the supply allotment $\hat{s}_i = s_i \frac{\mu_i+\mu_{i+1}}{\sum_{j=i}^{N} \mu_j}$
    Determine $\hat{x}_i$, the quantity of resource allocated to node i after observing its demand d_i: $\hat{x}_i = min\left\{\hat{H}(\hat{s}_i, d_i), \beta^{min}_{i-1} d_i\right\}$, where $\hat{H}(\hat{s}_i, d_i) = \hat{s}_i \frac{d_i}{d_i+(\mu_{i+1}+\delta_{i+1}\sqrt{\sigma_{i+1}})}$, and $\delta_{i+1} = \frac{\mu_i-\mu_{i+1}}{(\mu_i+\mu_{i+1})/2}$
    Update $\beta^i_{min} \leftarrow min\left\{\beta^{i-1}_{min}, \frac{\hat{x}_i}{d_i}\right\}$,and $s_{i+1} \leftarrow s_i - \hat{x}_i$
    $n \leftarrow n+1$
end while

3.2 Objective function formulation

Lien et al. [2014] considers the objective in the form of maximizing the expected minimum filling rate. Filling rate is defined as the amount allocated over demand of an agency corresponding to the literature. The objective function can be formulated as follows:

$$max\left\{\mathbb{E}[\beta_1, \beta_2 ... \beta_n]\right\} \tag{3.1}$$

n is the number of total agencies, and β_i is the the expected filling rate of the node i. They address that equity can be improved by increasing the filling rates of all agencies. Based on the objective, the TND allocation policy is developed and proved to be effective in settings with uncertain supply and demand, and the sequencing heuristic that sequencing in decreasing order of coefficient of variations is proposed.

The waste is not always reduced by only aiming at maximizing the minimum filling rate of a route. Therefore, instead of sequencing nodes in decreasing order of coefficient variations when determine the best visiting route, our research develop a new objective function to minimize the filling rates gaps among the agencies under the TND allocation rule. The gap of filling rate is defined as the difference between the maximum and the minimum filling rate within a route. We propose that equity can be achieved by minimizing the gaps among the agencies. And by following the TND allocation rule, which is developed based on the objective of maximizing the minimum filling rate, the balance between equity and waste can be maintained since the filling rates of all agencies are controlled to be at a high level at the same time and thus improve the overall resource utilization.

In our sequencing heuristic, given a quantity of supply, the sequence with the minimum gaps achieves equally distribution and effective use of resource. We determine the sequence with optimal equity by minimizing the filling rate gaps, therefore the objective is considered in the form of:

$$max\left\{\mathbb{E}[\sum_{i=1}^{n} log(\frac{\beta_i}{\sum_n^{j=1}\beta_j})]\right\} \tag{3.2}$$

β_i is the the expected filling rate of the node i. For a n-node network, the optimal sequence is found by comparing the objective function of all $N!$ sequences under the TND allocation policy. For each possible sequence, we generate an amount of instances according to the distribution of donation and demand quantities. The expected filling rate of each agency is returned after the simulation. The sequence with the largest objective value is chosen as the optimal sequence.

To better understand the relation between the objective value and the performance, we use a scaler to control the value in [0,1]. Therefore, the objective function is modified as follows:

$$max\left\{nlog(n)/\mathbb{E}[\sum_{i=1}^{n} log(\frac{\beta_i}{\sum_n^{j=1}\beta_j})]\right\} \tag{3.3}$$

The function determines how equally distributed of the fillings rates in a sequence. If the object value of a sequence is 1, the filling rates of all the agencies are exactly the same. If the value is near 0, then there are huge fillings rates gap among the agencies along the route.

To test the effectiveness of the new objective function, we apply the sequencing heuristic in Lien et al. [2014] and our sequencing heuristic in the real network of food bank to evaluate the performances of the different solutions obtained and determine whether our objective function achieves waste reduction.

3.3 Experimental design

The real food allocation network in Ithaca is presented in Figure 3.1, which includes all agencies and the main resource of donation. We assume the truck is housed near the location of main resource. Due to the algorithm that exhaustively search every possible sequence($N!$), we have to limit the number of agencies to less than 7. Based on the data provided by Food Bank of Southern Tier, we filter the agencies in Ithaca area from 8 nodes to 5 nodes. In Figure 3.2 we present the experimental design for the network. Node D is the resource of donation, and the other 5 nodes representing 5 agencies are selected because their locations are close to each other, which is more accord with the setting that no travel distance constriction is considered. To comply with the

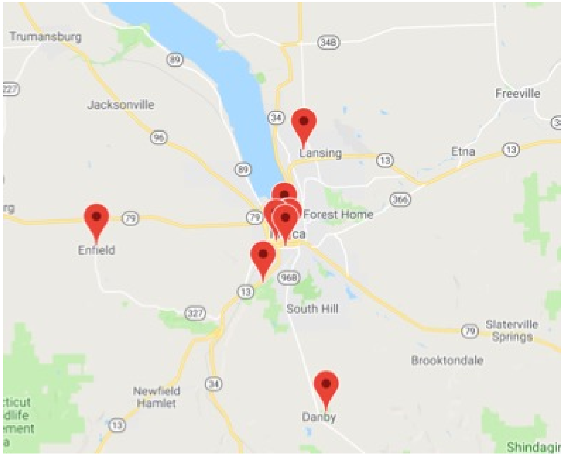

FIGURE 3.1. Food Bank network in Ithaca

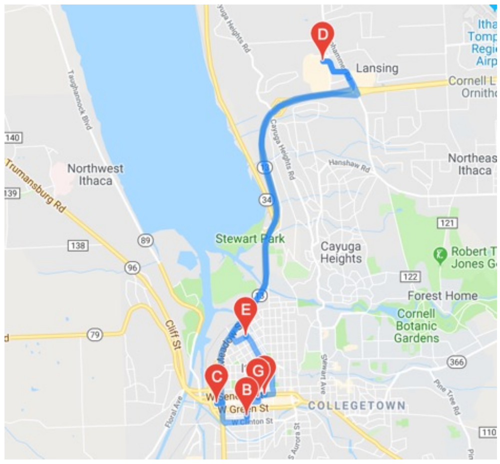

FIGURE 3.2. Experimental study

Table 3.1: Part of Donation

Donor	Weekly Donation
Target - Ithaca(part donations)	460

Table 3.2: Part of agencies poverty population and weekly demand

ID	Agency	Poverty Population	Weekly Demand (quantity)
G	Ithaca Kitchen Cupboard	14,136	225
C	Rescue Mission Pantry	7,091	170
F	Immaculate Conception Food Pantry	30,444	397
E	Baptized Church of Jesus Christ	19,112	118
B	Southside Community Center	2,129	33
	Total	72,912	943

reduction of demand, we reduce the supply available from the only donor in the base scenario. The ratio of available donations over all donations is the same as the the ratio of 5 agencies' demand over all agencies' demand.

3.4 Results and analysis

We establish a computational study to valuate and analyze the optimal sequence obtained by our objective function in Section 3.4.1. We also do a comparison between our optimal sequence and sequences in literature to understand the impact of different sequencing policies. Then a sensitivity analysis is studied by changing the quantity of donation, to gain the insight of the advantages of our objective function based on different levels of donation quantity.

Table 3.3: Results of Base Scenario

	Filling rate(%)	Waste(%)
Sequence 1	44.95%	1.85%
Sequence 2	44.92%	0.06%
Sequence with shortest path	43.40%	1.83%

3.4.1 Base scenario

A base scenario is performed to gain insight into the advantages of the optimal sequence obtained by using our objective function. A truck visits all 5 agencies every week after collecting donations. We generates 2 visiting sequences for the base scenario according to different objectives.

Sequence 1: Lien et al. [2014] address a sequencing heuristic that it is ideal to sequence nodes in decreasing order of coefficients of variation given a set of agencies in a route. In their heuristic, sequence nodes in decreasing order of standard deviation works when the coefficient variations are identical. The sequence obtained according to rule 1 is: $D-F-G-C-B-E-D$.

Sequence 2: Sequence 2 is determined by our objective function 3.3, which is aimed to minimize the gap among the filling rates of all the agencies and hence realize optimal equity. The sequence 2 is: $D-B-E-G-C-F-D$.

The results from base scenario form the baseline from which the values of other scenarios can be varied and generate different cases.

Additionally, in order to understand the importance of using a effective sequencing rule, another sequence is also investigated: the sequence with the shortest travel distance. The shortest path generated is presented in Figure 3.2. The truck departing from Node D, visit Node C, B, G, F, E sequentially. Our finding agrees with the work in Campbell et al. [2008] They proves that in a disaster relief environment, minimizing the total length of the route can lead to inequitable response times among demand locations served.

In the base scenario, we can evaluate and compare the performances of the two sequences in terms of expected minimum filling rate and expected used donations. The results are shown in 3.3. The evaluation parameters in terms of waste is defined as the quantity of unused waste over the total donation. The finding is that the two different sequences achieve almost the same expected minimum filling rate while sequence 2 effectively reduces expected waste. The expected waste in sequence 2 is only 3.5% of the waste in sequence 1. These results show that the sequencing determined by our objective function has better performance than the sequence using heuristic in Balcik et al. [2014], and also indicate that the our sequencing rule is an effective rule to

Table 3.4: Results for different donation quantity

State of donation		Filling Rate (%)		Waste (% to total donation)	
Pseudo state	Actual state (quantity)	Sequence 1	Sequence 2	Sequence 1	Sequence 2
50%	230	22.32%	22.41%	0.29%	0.00%
60%	276	22.41%	22.36%	0.22%	0.01%
70%	322	30.85%	31.00%	0.89%	0.02%
80%	368	35.83%	35.90%	1.20%	0.02%
90%	414	40.30%	40.44%	1.40%	0.03%
100%	460	44.95%	44.92%	1.85%	0.06%
110%	506	49.26%	49.13%	2.33%	0.20%
120%	552	53.47%	53.55%	2.45%	0.23%
130%	598	58.21%	58.25%	2.71%	0.46%
140%	644	62.94%	62.78%	3.12%	0.93%
150%	759	74.20%	74.23%	3.88%	1.88%
200%	920	88.76%	88.65%	6.78%	5.76%
250%	1150	98.33%	98.59%	18.55%	18.26%

determine the near-optimal visiting sequence.

Our finding also proves that only aiming to minimize the travel cost may result in inequitable allocation and leave more waste after serving all demands. Therefore, the impact of travel constraints should be more carefully considered in food resource allocation for nonprofit operation.

3.4.2 Sensitivity analysis

We establish other scenarios with change in supply quantity to valuate and compare the performances of the two sequences. To analyze the impact of changes in donation, the quantity is changed from 50% to 250% of the original donations in increments of 10%. This experimental settings may help understand the effectivenesses of different sequencing rules under different levels of donations. The states of donation are presented as a percentage change from the base scenario. The table 3.4 results describe the results for the SRA problem applying two different sequencing heuristics. The sequence 1 is determined by applying the sequencing heuristic from Lien et al. [2014], and the sequencing 2 is determined by our objective function 3.3. The performances of the two sequences are also valuated in terms of expected minimum filling rate and expected waste.

To analyze the performances when the supply is abundant, we set the state of donation to 250% of the donation in base scenario. Since the expected total demand for 5 agencies is 943, and the expected donation is 1,150, there is clearly enough supply available to meet the demands of all agencies.

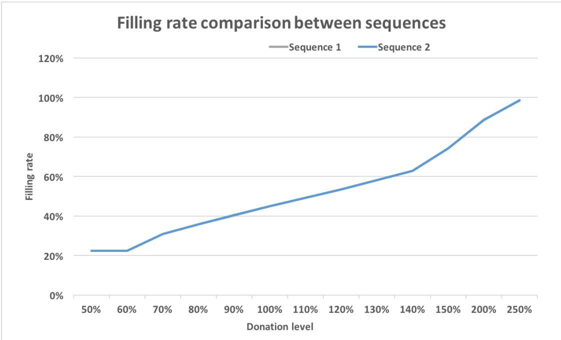

FIGURE 3.3. Filling Rate Comparison

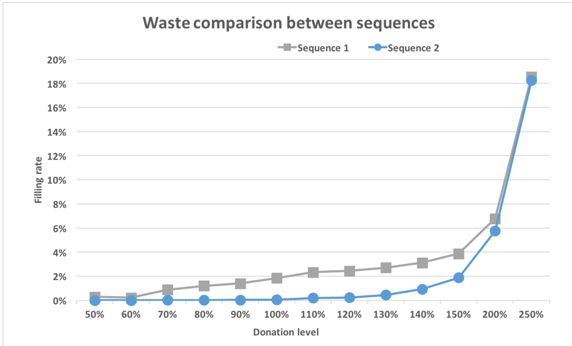

FIGURE 3.4. Waste Comparison

As shown on Figure 3.3, with the change in donation quantity, the difference between expected minimum filling rate of two sequences are very small. In Figure 3.4, the level of waste of two sequences are well controlled with the combination of TND allocation policy and sequencing algorithm. The TND allocation policy aimed at filling rates maximization ensures good performance of overall utilization, and the sequencing heuristics further reduce the waste while keeping equity. Figure 3.4 also shows that an obvious reduction in waste is achieved by our sequence comparing to the sequence in achieved by the other heuristic, and the reduction becomes less obvious in supply constrained states and supply abundant states.

In general cases, the level of food supply of food banks is neither too constrained nor too abundant. And in supply abundant states, although the percentage reduction in waste is small, a bit reduction can save a lot of resource since the total quantity is large in amount. Although the level of waste is not reduced significantly in terms of percentage of the total supply, the impact of a small reduction can be significant. Take the state with 150% of original donations for example, the expected waste of sequence 1 is 3.88% while the expected waste of sequence 2 is 1.88%. Based on the information in Table **??**, the weekly demand per person is 0.013. A small waste reduction in 2% saves 13.8 quantity of food, which can serve 1,070 people's demands completely. These results confirm that the sequence in our heuristic can reduce the waste while keeping the minimum filling rate. Achieving the minimum filling rates among agencies improves equity by reducing the difference between filling rates. Under the TND allocation policy, the overall distribution is improved and hence the goals of equity and low waste are achieved. These results achieved by our objective is appealing in the context of food allocation in nonprofit operation since it not only ensure a fair allocation, but also maximize resource utilization.

Chapter 4

Extended SRA Model

Sequencing nodes in different routes not only impact the filling rates and waste, but also impacts the travel distance and travel time. In early sections, we isolate the impact of travel cost, which is appropriate in the situations where all agencies are located in a dense area such as the network in Figure 3.2, or where travel costs are low compared to other costs (e.g. stopping costs). In some situations, the impact or restrictions of travel time/costs cannot be ignored. For instance, the locations of agencies that a truck must serve are scarcely distributed, a visiting sequence only aimed at maximizing equity may results in high travel cost and too long travel time. In such settings, it may be necessary and beneficial to find the optimal sequence that take travel costs into consideration.

In this section, we first present the modified model designed for objectives that both considers equity and efficiency (travel time/ costs). After modification, the method can be applied not limited to the network with 7 or less agencies. Then we do a case study with larger scale (i.e. network with 8 agencies) in the Food Bank network in Ithaca, an city served by Food Bank of Southern Tier and do analysis.

4.1 Modified model

To find a optimal solution in the settings where travel costs should be considered, we apply adaptive large neighborhood search approach to our model. Our heuristic consists of two stages. In the first stage, we extend Adaptive Large Neighborhood Search(ALNS) heuristic first proposed by Shaw [1998] and gradually improve the initial solution iteration to obtain successively better solutions. In ALNS algorithm, removal operators and insertion operators are predefined and used in every iterations in order to get a new solution. The decision whether to replace the

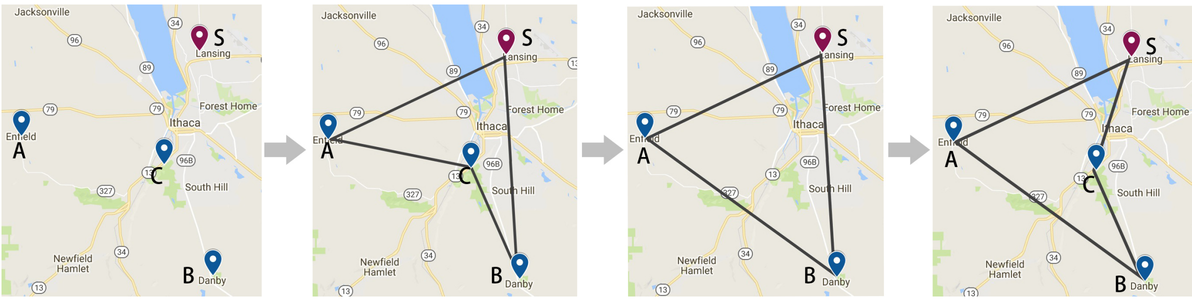

FIGURE 4.1. Depiction of the first stage of ALNS process

current solution is depends on the performance of the new one, which is done in the second stage. Probability distributions of operators are also updated according to the results. In our model, we partly borrow some operators from the literature and also create new operators according to our settings and objectives, which are discussed in Section 4.1.1. The first stage of extended ALNS process is illustrated in Figure 4.1. After obtaining an initial solution, which is a sequence starting from the warehouse node S, following the sequence of $A-C-B$ and going back to the warehouse. Then the agency node C is chosen and be removed from the current solution and then be inserted back to the network by the insertion operators also discussed in Section 4.1.1. The new solution is the sequence staring from the warehouse S, visiting A-B-C sequentially, and then going back to node S.

In the second stage, we determine whether to accept the new solution or not. An algorithm is run based on the resulting routing solution. The TND Heuristic Allocation Algorithm borrowed from Lien et al. [2014] finds the near optimal allocation solution to maximize the minimum filling rate given a visiting sequence. In order to take travel distance into consideration, an additional travel distance objective is incorporate to the utility function to valuate the performance of the sequential allocation on the resulting route. Let an utility function is modified as follows:

$$max\{\lambda_E U(E) + \lambda_T U(T)\} \tag{4.1}$$

where

$$U(E) = nlog(n)/\mathbb{E}[\sum_{i=1}^{n} log(\frac{\beta_i}{\sum_{n}^{j=1}\beta_j})] \tag{4.2}$$

$$U(T) = \frac{\sum_{a\in A} d_{sa}}{T} \tag{4.3}$$

$U(E)$ is the new objective function, referred to Equation 3.3, proved to be effective in realizing equity and reducing waste at the same time. $U(T)$ is the objective function aimed to minimize the total travel distance. λ_E denotes the weight of equity and waste objective, and λ_T denotes the weight for travel distance objective, such that $\lambda_E + \lambda_T = 1$. d_{sa} is defined as the distance between the warehouse s and the agency a. T represents the total travel distance of the solution sequence.

For each resulting solution, we calculate the two objective values in the simulation and evaluate the overall performance according to the parameters and variables.

Large value of λ_E means the equity is more likely to achieve feasible visiting sequences with high minimum filling rate, which may be at the expense of high travel cost. Similarly, large value of λ_T may lead to feasible visiting sequences with a short travel distance, which may also be at the expense of large optimality gaps of equity.

We present the pseudo code of framework of adjusted ALNS algorithm in Algorithm 2. The algorithm returns the best sequence found after a certain number of iterations according to our utility function 4.1 .

Algorithm 2 Framework of ALNS

input: Removal operators, insertion operators
output:Best visiting sequence

Initialize probability for each removal operator P_t^r and probability P_t^i for each insertion operator
Let T be the temperature and t be the counter
$S_{current} \leftarrow S_{best} \leftarrow S_{init}$
while $t < T$ **do** ▷ T: maximum number of iterations
    Select a removal operator $r \in R$ with probability P_t^r
    Let S_{temp} be the solution after applying removal operator r to $S_{current}$
    Select a insertion operator $i \in I$ with probability P_t^i
    Let S_{new} be the solution after applying insertion operator r to S_{temp}
    if $U(S_{new}) > U(S_{current})$ **then**
        $S_{current} \leftarrow S_{new}$
    elseLet $v \leftarrow e^{U(S_{new})-U(S_{current})/T}$
        Generate a random number $\epsilon \in [0,1]$
        if $\epsilon < v$ **then**
            $S_{current} \leftarrow S_{new}$
        end if
    end if
    if $U(S_{current}) > U(S_{best})$ **then**
        $S_{best} \leftarrow S_{current}$
    end if
    $T = hT$
    Update probabilities using the adaptive weigh adjustment procedure
    $t \leftarrow t + 1$
end while

4.1.1 Removal and insertion operators

In the first stage, we predefine 3 different removal operators for our algorithm, the first two are approached or used in Pisinger and Ropke [2007] and Demir et al. [2012] and the third one related to filling rate is created to be better accord with equity-based objective. For the insertion operator, we use greedy insertion (GI), which is adapted from Ropke and Pisinger [2006].

We now present the removal operators used in our model:

1. **Random removal(RR)**: This operator randomly removes a node from the solution , which helps diversify the search mechanism.

2. **Worst-distance removal(WDR)**: The operator removes the longest travel distance agency. The travel distance of each node in the operator is defined as the distance between the node with the previous one.

3. **Worst-satisfaction removal(WSR)**: The satisfaction level is defined as the evaluation parameter indicating the serving performance of each agency. The level of satisfaction is positively related to filling rate of the agency. This operator iteratively removes the agency with lowest level of satisfaction, which has the lowest filling rate among all agencies.

Then we present the insertion operator adapted in the algorithm:

Greedy insertion: This operator iteratively insert a node into the best position. It simulate every possible position for the insertion and valuate the performance of the possible sequence. The best position among the n possible positions (including the original position) is selected when the maximum utility is realized during the iteration.

4.1.2 Adaptive weights adjustment

After each iteration, we update the weight of the operator i according to the updated scores as follows:

$$w_{i,t+1} = w_i(1-r) + r\frac{score_i}{\theta_i} \tag{4.4}$$

$score_i$ denotes the score of the operator i, and θ_i is the total number of times operator i has been used. The reaction factor r determines the speed of weight adjustments according to the latest result. The values of $\sigma_1, \sigma_2 and \sigma_3$ is defined as the expected setting $\sigma_1 \geq \sigma_2 \geq \sigma_3$, which is normally used to reward an operator with a good solution.

4.2 Case study

In our case study, we based on the data in city Ithaca provided by the Food Bank to evaluate the performance of the adapted ALNS algorithm in the 8-node network.

Table 4.1: Donation

Donor	Weekly Donation
Cornell University	895
Finger Lakes Fresh	12
Target - Ithaca	1,142
Wegman's - Ithaca #71	237
Walmart - Ithaca	262
BJ's Wholesale Club	1,493
Cornell University Taylor Hall	9
Total	4,050

Table 4.2: Agencies poverty population and weekly demand

Agency	Poverty Population	Weekly Demand (quantity)
Ithaca Kitchen Cupboard	14,136	225
Rescue Mission Pantry	7,091	170
Immaculate Conception Food Pantry	30,444	397
Enfield Food Distribution	43,210	7,025
Tompkins Community Action	9,824	251
Danby Food Pantry	6,561	105
Baptized Church of Jesus Christ	19,112	118
Southside Community Center	2,129	33
Total	132,507	8,324

4.2.1 Problem setting

According to the data in city Ithaca provided by the Food Bank of the Southern Tier, the donors' and agencies' profiles are provided in Table 4.1 and Table 4.2. All donations are collected and stored in the warehouse prior to visiting all 8 agencies. A truck is housed in a warehouse near Target (a main food resource in Ithaca). The truck visits all the agencies weekly, starting from the warehouse and comes back to the same location after visiting all 8 agencies.

4.2.2 Parameters setting

The values of parameters used in our modified ALNS algorithm are defined in Table 4.3. Similar to Demir et al. [2012] and Pisinger and Ropke [2007], we reward a global best solution more than a better solution, and we also reward a worse solution to diversify the research. In our case, the network is combined with 1 donor and 8 agencies, so we set the total number of iteration to 300 in terms of the size of the network and expected running time.

We let $\lambda_E = 0.5$, which denotes the weight of equity and waste objective, and λ_T is also 0.5, which denotes the weight for travel distance objective.

Table 4.3: Parameters used in ALNS algorithm

Parameters	Description	Values
N	Total number of iterations	300
σ_1	Score adjustment for new global solution	2
σ_2	Score adjustment for better solution	1
σ_3	Score adjustment for worse solution	0.5
r	Reaction factor determining speed of adjustment	0.1
P_{init}	Starting temperature	1
h	cooling rate	0.998

Table 4.4: Results with different iterations

Iterations	Utility	Valuation Indicators		
		Filling rate(%)	Waste(%)	Distance(km)
0	0.9312	46.29%	0.42%	44.42
20	0.9531	46.69%	2.44%	39.63
40	0.9559	46.12%	3.02%	40.00
60	0.9559	46.40%	3.02%	40.00
80	0.9587	45.82%	4.63%	38.56
100	0.9587	45.82%	4.63%	38.56
120	0.9587	45.82%	4.63%	38.56
140	0.9587	45.82%	4.63%	38.56
160	0.9587	45.82%	4.63%	38.56
180	0.9587	45.69%	4.63%	38.56
200	0.9602	45.38%	0.00%	42.00
220	0.9602	45.38%	0.00%	42.00
240	0.9602	45.38%	0.00%	42.00
260	0.9602	45.38%	0.00%	42.00
280	0.9602	45.38%	0.00%	42.00
300	0.9602	45.38%	0.00%	42.00

4.3 Computational results and analysis

We present computational results of case study in Table 4.4 to assess the performance of our model. Figure 4.2 shows the behavior of the heuristic for the 8-node network in Ithaca, and displays the way that best solution and new solutions change over 300 iterations. The utility of the best solution is increasing within a certain number of iterations and then the best solution remains the same after 200 iterations.

Initial solution is obtained by sequencing heuristic in Lien et al. [2014], which is the benchmark solution in the analysis. The table presents the performances of the best solutions found after every 20 iterations up to 300 in total. Since we incorporate efficiency (travel distance/ time) into our objective function, the best solution found after a certain number of iterations is not necessarily related with the highest minimum filling rate or lowest waste so far. For instance, the

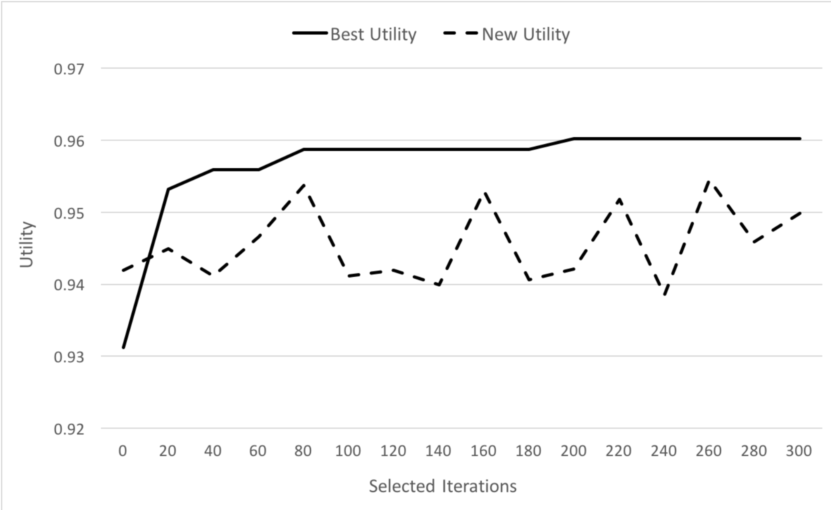

FIGURE 4.2. Solution utilities obtained by ALNS for a 8-node network in Ithaca

expected minimum filling rate of best solution obtained after 80 iterations is 0.47% lower than the initial while the travel distance is effectively reduced by 5.86km, which saves 13% travel distance of initial solution. In this case, the best solution remains the same after 200 iterations.

Compared to the initial solution obtained by applying heuristic in Lien et al. [2014], the overall performance of the best solution is 3% better than the initial solution according to our objective function. The best solution found by our method not only achieves smaller filling rate gap, but also realizes waste reduction at a low cost of reducing the minimum filling rate. Food saved by a small reduction in waste can serve more people in need. Also, the solution saves 6% of the travel distance of the initial route. This improvement is not only beneficial to reducing travel costs, but also make the resource allocation routine more efficient.

As shown in Table 4.4, the adjusted ALNS heuristic performs well on the 8-agency network in our case and the extended operators and parameters defined in our model work well to gradually improve the overall performance of the solution.

To be better applicable to others case, parameters can be adjusted according to the need, and operators can be extend or modified to comply with different operating contexts. For example, the weight of equity λ_E and weight of travel cost λ_T can be adjusted according to the location distribution of agencies and donors. Situations where agencies are scarcely distributed and far from each other may encourage to put more weight on the travel cost. On the contrary, when all the agencies are located in a dense area and stopping costs are higher compared to travel costs, it is rather reasonable to put more weight on λ_E.

The network in Ithaca is combined with 8 agencies, and the near optimal solution is found with a reasonable computing time. The speed of finding a near-optimal solution is much efficient than the exhaustive research, which needs to go through $N!$ possible sequences and choose the sequence with the largest utility. Our heuristic can be better evaluated when applicable to the networks with more agencies and intuitively more iterations need to be done to get better solution.

CHAPTER 5

Conclusions and Future Directions

This research developed a model for Sequential Resource Allocation problem aimed to maximize equity with a different objective function, which not only realize the maximization of minimum filling rate within the agencies served, but also effectively reduce the waste. The experimental study proves that the new objective function performs well in maximizing the minimum filling rates and reduce expected waste effectively.

Our work also incorporate travel constraints for the situations where travel costs cannot be ignored. And we also also extend the sequencing method by applying Adaptive Large Neighborhood Search (ALNS), which make it applicable to the cases where number of agencies is 7 or more. Model in the literature limits the problem to sequence of 6 or less because the optimal sequence is found by comparing the utilities of all $N!$ sequences. Results prove that the adjusted ALNS algorithm works effectively and efficiently in finding a near-optimal solution in the resource allocation problem, which achieves realizing equity maximization, effective resource utilization and efficient operations. The heuristic is flexible and adjustable to fit in different situations by changing the weights of valuation parameters, changing the parameter value and modifying functioning operators in the algorithm.

These results are useful for nonprofit operations such as food banks facing the task of improving the equity of resource allocation with uncertain supply and demands and in the need of maximizing resource utility due to limited resource.

Our research is modeled for single commodity and single vehicle problem, therefore an extension can be make to consider multiple commodities or multiple vehicles. In the multiple commodities settings, demands can be make according to different categories such as meat and vegetables. Additionally, resources can be categorized to perishable and imperishable, and the supply remained after visiting all agencies can treated differently because imperishable items can be redistribute in the next time. Moreover, for future research it would be an interesting area to study dynamic allocating and sequencing. Our simulation use the fixed data in fiscal year 2017 to generate normal distributed donations and demands. In reality, the distribution is always changing due to internal and external reasons. For instance, in dynamic allocation and sequencing rule, the estimation of demand of an agency can be formulated to a prediction function that considers poverty population and weather factor. Therefore, keeping track of data of agencies and donors is needed to better analyze and predict the tendency of donation and demand, hence helps make better decisions.

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